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Avoidance in negative ties: Inhibiting closure, reciprocity, and homophily

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Avoidance in negative ties: Inhibiting closure, reciprocity, and homophily

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ABSTRACT

Theorising of negative ties has focused on simplex negative tie networks or multiplex signed tie networks. We examine the fundamental differences between positive and negative tie networks measured on the same set of actors. We test six mechanisms of tie formation on face-to-face positive (affect/esteem) and negative (dislike/disesteem) networks of 282 university students. While popularity, activity, and entrainment are present in both networks, closure, reciprocity, and homophily are largely absent from negative tie networks. We argue this arises because avoidance is inherent to negative sentiments. Avoidance reduces information transfer through negative ties and short-circuits cumulative causation.

1. Introduction

Negative ties are an important and emerging field of social network research. They exist in a wide range of human social interactions, from playground bullying to interstate wars. The focus of previous research has tended to be on one of two types of negative tie networks: researchers have either modelled simplex negative tie networks (Lim and Rubineau, 2013; Papachristos et al., 2013), or they have modelled multiplex signed tie networks (Kalish, 2013; Epstein, 1979; Mower-White, 1977, 1979; Truzzi, 1973; Newcomb, 1968; Doreian and Krackhardt, 2001; van de Rijit, 2011; Ilany et al., 2013; Berger and Dijkstra, 2013; Huitsing et al., 2014; Rambaran et al., 2015). We believe, however, that there is an important area of research that has only received limited study: the comparison of positive and negative tie networks on the same set of social actors (Ellwardt et al., 2012; Boda and Néray, 2015). Such a comparison allows one to directly compare the underlying mechanisms driving positive and negative ties, and therefore helps us to understand exactly what is unique about negative tie social dynamics.

We present an exploratory study of the mechanisms driving positive and negative ties, with a particular focus on how they may differ. We model four Exponential Random Graph (ERG) models on the same set of actors, and find that of the six major mechanisms examined, three are largely absent from the negative tie networks: closure, reciprocity, and homophily.

We argue that the primary reason why negative tie mechanisms are different from positive tie mechanisms is because the concept of avoidance is inherent to negative ties. When we feel negative sentiment towards someone, our general tendency is to avoid them, rather than remain proximate which may antagonise both ourselves and them. This avoidance inherent in negative ties leads to low information transfer. In the case of closure, the enemy of an enemy is so distant as to be a random stranger. In the case of reciprocity, because the sender of a negative tie tends to actively avoid the recipient, the recipient is likely to remain unaware of the sender and the tie, and generally no more likely to reciprocate than at random. Avoidance – because it reduces contact with antagonistic tie partners – also short-circuits cumulative causation in negative ties. In the case of homophily, by avoiding those who are dissimilar to us, we stop small negative sentiments or differences from escalating into negative ties.

The rest of this paper is structured thus. First, we provide a literature review, in which we review approaches to modelling negative ties, and overview the literature around the six mechanisms we propose to examine. We also briefly examine the literature on the role of avoidance in negative ties. Second, we outline our methods and data, explaining how we estimate (1) two multiplex ERG models, one on positive tie networks (affect/esteem) and one on negative tie networks (disaffect/disesteem), and (2) another two signed multiplex ERG models, one on affect networks (affect/disaffect) and one on esteem networks (esteem/disesteem). In this section we also explain how we analyse the significant parameters so as to identify the key differences in mechanisms

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underlying tie formation in positive and negative tie networks. Third, in Sections 4–6 we present the outcomes of our analysis, as well as our interpretation of the results in light of previous research.

2. Literature review

This literature review has three parts: First, we review approaches to modelling negative ties. We argue that there are three main approaches: (1) modelling positive and negative ties in the same model, (2) modelling negative ties on their own, and (3) modelling positive ties and negative ties separately, then comparing their dynamics. As mentioned in the introduction, this paper focuses on the third approach, as our motivation is to understand how the dynamics of positive and negative ties differ in fundamental ways. However, for completeness, we also apply the first approach, as we want to show that the results do not substantially differ based on the modelling choice.

The second part of the literature review focuses on six main mechanisms that are said to drive tie formation: closure, reciprocity, homophily, popularity, activity, and entrainment. In doing this, we review the importance of each of these mechanisms in both positive and negative tie networks.

The third part of the literature review briefly introduces the concept of avoidance as a mechanism which potentially interrupts the formation of negative ties.

2.1. Approaches to modelling negative ties

The dominant approach to modelling negative ties has traditionally been to model them as signed ties, with positive and negative ties in the same network. This approach dates back as early as 1946, when Heider proposed the *theory of structural balance* to explain sentiment relations in dyadic and triadic relationships (Heider, 1946). His main theory was that entities (which may include people) are likely to form signed ties (i.e. positive/negative ties) in a pattern that avoids cognitive dissonance (Hummon and Doreian, 2003; Taylor, 1967; Zajonc, 1960; Cartwright and Harary, 1956; Heider, 1946). Since Heider, there has been a number of studies testing balance theory by modelling signed tie networks, though the evidence is mixed at best (Kalish, 2013; Epstein, 1979; Mower-White, 1977, 1979; Truzzi, 1973; Newcomb, 1968; Doreian and Krackhardt, 2001; van de Rijit, 2011; Ilany et al., 2013). Another more recent theory that has adopted a similar approach of modelling signed ties is *status theory*. Applied by Leskovec et al. (2010), the theory stems from the observation that signed ties may be interpreted differently based on the intent of the sender (Guha et al., 2004). It suggests that signed tie formation may be driven by other mechanisms than cognitive consistency – with positive ties sent to actors of higher status and negative ties sent to those of lower status. For the most part, status theory has been presented as an alternative paradigm to Heider's balance theory.

With negative ties gaining more attention in recent decades, modelling negative ties on their own is fast becoming another popular approach. Theoretically, papers that adopt this modelling technique have addressed a wide range of questions, from the role of status in negative tie networks of university students in residential programs (Lim and Rubineau, 2013), to the role of geography and reciprocity on gang violence (Papachristos et al., 2013).

Finally, the least common approach is the modelling of positive and negative ties separately, generally on the same set of actors, and generally in order to compare the dynamics of positive and negative tie formation. Boda and Néray (2015) modelled positive and negative ties separately and found that differences in ethnicity drove both positive and negative tie formation, though it was stronger in the positive tie network. Ellwardt et al. (2012) separately modelled positive and negative gossip networks at work and found that the negative network was notably hierarchical compared to the positive network.

2.2. Mechanisms of tie formation

In this section we review literature focusing on the last five years. We organise this section around the six major mechanisms identified in Lusher and Robins (2013a,b). Our later analysis is based on this same categorisation of mechanisms.

2.2.1. Closure

Closure is the tendency for one's tie partners (or tie partner's tie partners) to form a tie (Lusher and Robins, 2013a,b). The classic example of this is the formation of the triad when one's two tie partners form a relationship (i.e. the base of the triangle). Within social network modelling, closure is represented by a range of triadic network effects, and four-cycle (multiple two-paths) network effects. These include the transitive triad (which represents a hierarchical group formation), cyclical triads or three-cycles (which represents egalitarian group formation), and various versions of the four-cycle (Lusher and Robins, 2013b).

Recent literature has generally found that negative tie triadic closure is weak or completely absent, while positive tie triadic closure is present. Meanwhile, evidence on four-cycle closure effects is mixed or contradictory: positive tie networks tend to show anti-closure for multiple two-paths (a type of four-cycle) but not necessarily for other four-cycle parameters (such as shared in-ties and shared out-ties) (Ellwardt et al., 2012; Huitsing et al., 2012; Boda and Néray, 2015).

Interestingly, Papachristos et al. (2013) found strong triadic anti-closure and four-cycle closure in homicides, but no significant triadic or four-cycle closure effects in their networks of fatal and non-fatal gang shootings. The difference in finding from other literature may stem from the different and extreme nature of the negative ties involving homicide.

2.2.2. Reciprocity

Reciprocity is the tendency for the recipient of one's tie to return that tie, whether of a similar or different sign (Lusher and Robins, 2013a,b). The classic example of this is mutual friendship where two actors direct a positive tie to each other. There are also more complex reciprocity effects available in social network modelling, including reciprocated negative ties, and reciprocated mixed ties, where a tie of one flavour (say friendship) is returned with a tie of another flavour (say status).

Existing literature finds reciprocity in positive tie networks as well as negative tie networks (Papachristos et al., 2013). Comparative studies of positive and negative ties on the same actors find mixed results: some studies find reciprocity is stronger in the negative network (Ellwardt et al., 2012), and others find it is stronger in the positive network (Huitsing et al., 2012; Boda and Néray, 2015).

2.2.3. Homophily

Homophily is the tendency for actors to send ties to other actors with similar values for an attribute (Lusher and Robins, 2013a,b). The classic example of this is where one prefers to befriend those of the same gender. Homophily can exist on a wide range of attributes, including demographic traits (like race), personality traits (like extroversion), behavioural traits (like deviancy), and geography. The polar opposite of homophily is heterophily, where opposite values for an attribute predict the formation of a tie. For example, heterosexual romantic love is heterophilous on gender.

In this paper, we refer to homophily as a category containing related, but not identical mechanisms and effects. This is the same as other categories, such as closure, which encompasses both triadic and four-cycle closure, and anti-closure. Likewise, we subsume into the category of homophily both positive tie homophily (attraction to similar others), negative tie homophily (dislike of similar others), and positive and negative tie heterophily (attraction/dislike of dissimilar others). The point of such categorisation is not to say the effects or mechanisms are identical, but rather that they are likely to share common traits.

In general, homophily is found in both positive tie networks and negative tie networks (Ellwardt et al., 2012; Young and Weerman, 2013; Lusher and Robins, 2013b; Nieuwenhuis et al., 2013; Jaspers et al., 2013; Papachristos et al., 2013). Some studies that have compared positive and negative tie networks on the same actors have found homophily to be stronger in their positive tie networks. For example, Boda and Néray (2015) found homophily on gender and ethnicity in the positive tie network but only homophily on ethnicity in the negative tie network. Furthermore, the homophily effect in the negative network was slightly weaker.

2.2.4. Popularity

Popularity is the tendency for those receiving ties to receive additional ties (Lusher and Robins, 2013a,b). This is essentially a correlation between an existing in-degree and future in-degree. The classic example is the preferential attachment seen on the Internet where top-trending sites tend to receive even more hyperlinks (Barabási and Albert, 1999). Within social network modelling, popularity tends to be represented by in-star social network effects.

The literature on popularity has tended to focus on positive ties, with an enormous number of articles demonstrating the operation of popularity and/or preferential attachment in a wide range of social networks. Within the negative tie literature, a number of studies have found the presence of popularity effects, including in massive multiplayer online games (Szell et al., 2010), negative gossip networks (Ellwardt et al., 2012), and professional/work relationships (Daly and Moolenaar, 2013; Carboni and Casciaro, 2013). What is most interesting, however, is that there are several studies which have found (or argue) that popularity is weaker in positive tie networks, and generally stronger in negative networks (Ellwardt et al., 2012; Lim and Rubineau, 2013; Szell et al., 2010).

2.2.5. Activity

Activity is the tendency for those sending ties to send additional ties (Lusher and Robins, 2013a,b). While popularity tends to be a measure of the operation of status in a network, activity is about differing levels of tie initiation amongst the actors within a population. We might think of differences in activity as being driven by internal traits of actors such as tendencies towards extroversion and introversion. Within social network modelling, activity tends to be represented by out-star social network effects.

Literature on activity is more sparse. Interestingly, while Ellwardt et al. (2012) found no activity effects in either positive or negative gossip networks, both Boda and Néray (2015) and Lim and Rubineau (2013) argue that activity tends to be stronger in negative tie networks.

2.2.6. Entrainment

Entrainment is the tendency for ties of one flavour (e.g. friendship) to predict ties of another flavour (e.g. esteem) (Lusher and Robins, 2013a,b). An example is where friendship begets romantic love. In social network modelling, this is simply represented by two ties of different flavours being directed from and to the same pair of actors.

Within the literature, the study of entrainment is relatively limited as it requires multiplex data on different types of ties. However, we can infer some potential entrainment from the existing literature, especially those with attribute data. For example, Ellwardt et al. (2012) finds that negative gossip tends to be directed towards those which one has contact with, and also to be directed to those of lower social status. In these two cases, contact frequency and social status may be thought of as a parallel network; and thus negative gossip may be thought of as entrained with contact or status.

2.3. Avoidance and negative ties

In this paper we argue that much of the difference between negative and positive tie networks can be explained by the human tendency to avoid those with whom we feel negative sentiments. Intuitively this notion of avoidance makes sense: negative ties tend to be costly and a violation of social norms. Unless there is a situation of predation, or the impossibility of exit, we would expect that a negative sentiment results in repulsion and social distance.

While this concept of avoidance has only been briefly addressed in the negative tie literature (Grosser et al., 2010; Labianca and Brass, 2006; Rambaran et al., 2015), the academic literature, particularly from social psychology, has addressed the broader issue of avoidance in human relationships, with multiple studies finding that humans tend to create distance with those we dislike (Jehn, 1995; Paladino and Castelli, 2008). In social network studies, including our own, desire to avoid is often used as the operationalisation of negative ties, suggesting that the two concepts are intimately related (Labianca and Brass, 2006).

3. Methods and data

3.1. Dataset

This is the second paper in a series using this dataset. For ease of reference, we have reproduced the description of the dataset from our first paper (Yap and Harrigan, 2015). The information which follows in Section 3.1 is repeated verbatim from the first paper, except for the notes in square brackets:

Our dataset was drawn from the final two years of a medium sized Singaporean business university. The students represented two cohorts of students from a bachelor of social science. [The data was collected in January 2013, within the first two weeks of the new semester. The survey took approximately 5 minutes to complete.] All 298 students in the selected cohorts were sent the survey and 282 (94.5%) completed the survey. This is a very high response rate, even for a social network survey.

The final dataset included only the 282 respondents. The 16 non-respondents and any ties to them were removed.

Students were recruited using multiple methods: they were sent emails, and then multiple reminder emails. They were also encouraged to do the survey during class time, and given a $5 incentive to do the survey. The survey was done online to make the survey both easier for respondents to complete, and easier for us as surveyors to enter and clean the data. [The survey was done without supervision by researchers, teachers, or others. Most surveys, we presume, were completed when respondents were checking email at home or at university.]

The mean age of respondents was 22.7 years [with a standard deviation of 1.43 years]. Respondents were approximately evenly split between 3rd and 4th year students. We chose the 3rd and 4th year cohorts because they had had the longest period of continuous contact with one another: The 3rd years had known each other for approximately two and a half years, and the 4th years had known each other for approximately three and half years. The Bachelor of Social Science itself, is very much like a small liberal arts college in Singapore, with small, seminar-style classes, and close student–student, and student–teacher interactions. We felt that this would mean that social network effects would be particularly strong after 2–3 years of their development. From a balance perspective (Heider, 1946; Cartwright and Harary, 1956), one would expect that 2–3 years should give time for the effects of balance to be able to 'sort themselves' and become apparent.

Alongside a range of demographic questions (gender (Binary), age (Continuous), race (Categorical), first major (Categorical), membership of executive committee of student society (Binary), family income (Continuous)), students were asked four social network questions. It should be noted, that we originally asked much more abstract questions about friendship and esteem. However, when we did ethnographic pretesting of our surveys, we found that these questions produced very poor responses from interviewees. The problem was that interviewees had trouble knowing exactly what we meant by these abstract terms like 'friendship' or 'esteem'. We workshopped the questions with multiple focus groups, and found that 'proxies' – concrete hypothetical situations – were felt by the majority of participants to be much easier to understand, and also best captured the dimensions of friendship and esteem we were targeting. We also found that students were both more likely to answer, and answered the questionnaire more quickly (response time was reduced threefold), when they were given concrete hypothetical situations. Our final questions were:

1. Who would you invite for lunch?
2. Who would you avoid having lunch with?
3. Who would you nominate to lead the students' council?
4. Who would you avoid nominating to lead the students' council?

These four questions are asked as proxies for (1) like/positive affect, (2) dislike/negative affect, (3) esteem/admiration, and (4) disesteem/disdain.

For each question, the students were asked to nominate between one and five other students in their year/cohort (i.e. 3rd years could only nominate 3rd years, and 4th years only other 4th years). A minimum of one nomination was included to try to overcome the negative and potentially costly action of nominating other students for the negative ties (questions two and four). The literature on forced response questions (Russell, 1993; Stieger et al., 2007) says that there are two main potential problems with forced responses: (1) it decreases response rate, and (2) if respondents are expressing an opinion about something they have no knowledge of their answers would reduce the accuracy of the survey. In our case, the first problem did not occur: we had a 94.5% response rate. The second problem, we felt, was not an issue as the students had known each other, and had taken numerous classes together, for at least two and a half years. Informal post-survey interviews with students suggested that the vast majority had no problem with the forced response, with a small minority (15 people) making either one self-nomination or nominating the first person (like a donkey vote) on the survey. This amounted to 19 ties (nominations), and we removed these ties (not the individuals, just the ties) from the dataset and coded them as empty ties. [We also removed negative-tie nominations where participants nominated the same person for both the positive and negative ties in the same network (like/dislike or esteem/disesteem), since (1) it was meaningless to both want to go to lunch (nominate for students' council) and want to avoid going to lunch (avoid nominating) with the same person; and (2) qualitative, post-survey interviews with respondents confirmed that this technique was used to deliberately avoid nominating a negative tie, and that the initial positive tie nomination was real.]

What makes lunch an operationalisation of friendship and dislike? Through our qualitative interviews, we found that lunch was seen as a good proxy for friendship simply because eating a meal is a necessity, and it is a social situation that can be shared with people whose company you like. What makes nomination to lead/not lead students' council a measure for esteem/disesteem? Through our qualitative interviews we found that the peer nomination question 'Who would you nominate for to lead the students' council?' was a good proxy for esteem because nominating someone for student council is an act of indicating that you hold them in high respect, for a public office with limited number of positions.

We further tested our operationalisation of friendship and esteem by undertaking a short survey of 448 students from the same university [which showed that these questions effectively operationalised friendship and esteem (for full description of this study, please see our previous study (Yap and Harrigan, 2015))].

3.2. ERG modelling

We estimate the dynamics of positive tie formation and negative tie formation using ERG modelling. ERG models estimate the probabilities for creating or terminating ties in a network using a model of tie formation that is similar to a standard logistic regression. The outcome variable is the formation (or not) of a single tie, the predictor variables are the subgraphs formed by other ties in the network, and the attributes of the actors in the network (Wasserman and Pattison, 1996; Snijders, 2002; Snijders et al., 2006; Robins et al., 2009). The major difference between an ERG model and a standard logistic regression model is that observations in an ERG model are assumed to be interdependent, i.e. the formation of network ties is dependent on the other network ties in the graph. This method allows us to evaluate the effect of complex subgraphs on tie formation, while controlling for lower order (i.e. simpler) subgraphs.

We compare the dynamics of positive tie formation with the dynamics of negative tie formation using four distinct models: Model 1, the positive network (affect/esteem); Model 2, the negative network (disaffect/disesteem); Model 3, the signed affect network (affect/disaffect); and Model 4, the signed esteem network (esteem/disesteem). We are forced to estimate four models of two networks each, rather than the four networks as one model because the software (XPNet) only allows two networks to be modelled at one time.

Table 1 summarises the key subgraphs used in our positive tie model (Model 1) and negative tie model (Model 2). Descriptions of the subgraphs in Models 3 and 4 can be inferred through substitution of A ties as affect/esteem, and B ties as disaffect/disesteem.

We use a special multiplex software called XPNet to estimate the interaction between the two networks in each model (Wang et al., 2006a,b; Wang, 2013; see also Robins et al., 2011). XPNet estimates ERG models using Monte Carlo Markov Chain Maximum Likelihood Estimation (MCMCMLE) (Snijders, 2002). XPNet allows us to model two interdependent networks that exist on the same set of actors in the one model. This modelling accounts for and measures both the intranetwork effects (e.g. within the affect network itself), and internetwork effects (e.g. between affect and esteem networks).

XPNet (and ERG models) estimate a model of the form (Koskinen and Daraganova, 2013):

$$P(x_{ij} = 1|\boldsymbol{A}, \boldsymbol{B}) = \frac{1}{1 + e^{-1(\beta_1 s_1 + \beta_2 s_2 + \cdots + c)}} \qquad (1)$$

By modelling two networks in the same model, XPNet controls for interaction effects between the various networks. In Models 1 and 2, the model takes into account the interdependence of ties of positive affect on positive esteem, and similarly for negative ties. Modelling this interdependence makes intuitive and theoretical sense, since we know that in a real face to face network these two relations are rarely independent. We tend to admire our friends,

Table 1
Key parameters included in positive tie model (Model 1: affect/esteem) and negative tie model (Model 2: disaffect/disesteem).

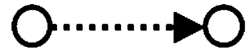
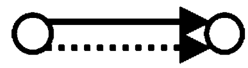
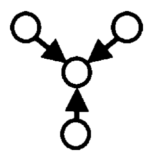
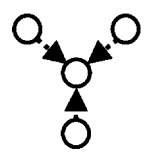
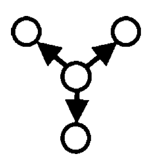
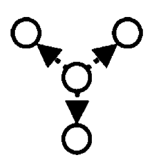
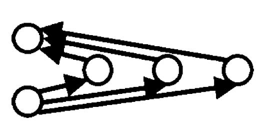
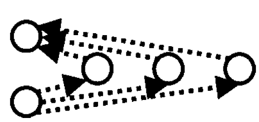
Name	XPNet Parameter	Diagram	Description
Tie	ArcA[*]		Sending a friendship tie
	ArcB[*]		Sending an esteem tie
Entrainment	ArcAB		Simultaneous sending of a friendship tie and an esteem tie
Sinks	SinkA		Receiving friendship tie(s) but not sending any friendship tie(s)
	SinkB		Receiving esteem tie(s) but not sending any esteem tie(s)
Sources	SourceA		Sending friendship tie(s) but not receiving any friendship tie(s)
	SourceB		Sending esteem tie(s) but not receiving any esteem tie(s)
Isolates	IsolatesA		Neither sending nor receiving any friendship tie(s)
	IsolatesB		Neither sending nor receiving any esteem tie(s)
Alternating In-Stars	In-K-StarA		Weighted sum of all friendship in-stars where effects of higher order stars are dampened
	In-K-StarB		Weighted sum of all esteem in-stars where effects of higher order stars are dampened
Alternating Out-Stars	Out-K-StarA		Weighted sum of all friendship out-stars where effects of higher order stars are dampened
	Out-K-StarB		Weighted sum of all esteem out-stars where effects of higher order stars are dampened
Alternating Transitive 2-Paths	A2P-TA		Weighted sum of all transitive friendship 2-paths where effects of edges sharing the same base nodes are dampened
	A2P-TB		Weighted sum of all transitive esteem 2-paths where effects of edges sharing the same base nodes are dampened
Homophily	rbAforAttribute_Gender		Increased probability of a friendship tie where both actors are of the same gender
	rbAforAttribute_Exec		Increased probability of a friendship tie where both actors are in the executive committee/where both actors are not in the executive committee
	SameCategoryArcA forAttribute_First_SOSS_Major		Increased probability of a friendship tie where both actors share the same major

Table 1
(*Continued*)

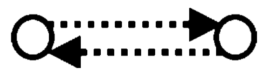
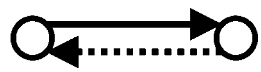
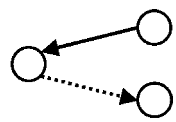
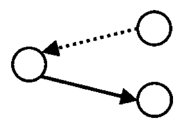
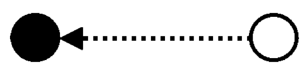
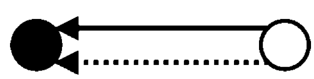
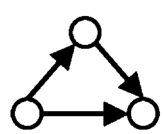
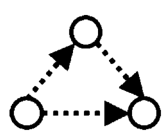
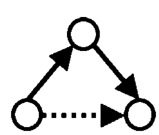
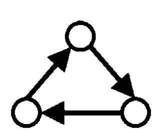
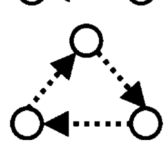
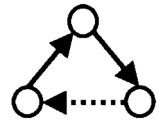
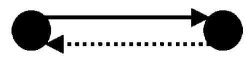
Name	XPNet Parameter	Diagram	Description
	rbBforAttribute_Gender		Increased probability of an esteem tie where both actors are of the same gender
	rbBforAttribute_Exec		Increased probability of an esteem tie where both actors are in the executive committee/where both actors are not in the executive committee
	rbSumBofContinuous Attribute_Age		The greater the sum of the age of both actors the greater the probability of an esteem tie
Reciprocity	ReciprocityA		Returning a friendship tie with a friendship tie
	ReciprocityB		Returning an esteem tie with an esteem tie
Mixed Reciprocity	ReciprocityAB		Returning a friendship tie with an esteem tie, and vice versa
Mixed 2 Stars	Mixed2StarAB		Receiving a friendship tie and sending an esteem tie
	Mixed2StarBA		Receiving an esteem tie and sending a friendship tie
Popularity	rrAforAttribute_Exec		Increased probability of receiving a friendship tie if an actor is in the executive committee
	rrBforAttribute_ Gender		Increased probability of receiving an esteem tie if an actor is female
	rrBforAttribute_Exec		Increased probability of receiving an esteem tie if an actor is in the executive committee
Mixed Popularity	M-rrforAttribute_Exec		Increased probability of receiving entrained friendship and esteem ties if an actor is in the executive committee
Alternating Transitive Triads	AKT-TA		Weighted sum of all transitive friendship triangles where effects of edges sharing the same base are dampened
	AKT-TB		Weighted sum of all transitive esteem triangles where effects of edges sharing the same base are dampened
	TKT-ABA		Weighted sum of all mixed transitive triangles (friendship sides and esteem base) where effects of friendship ties sharing the same base are dampened
Alternating Cyclical Triads	AKT-CA		Weighted sum of all cyclical friendship triangles where effects of edges sharing the same base are dampened
	AKT-CB		Weighted sum of all cyclical esteem triangles where effects of edges sharing the same base are dampened

Table 1
(*Continued*)

Name	XPNet Parameter	Diagram	Description
	CKT-ABA		Weighted sum of all mixed cyclical triangles (2 friendship ties and 1 esteem tie) where effects of friendship ties sharing the same base are dampened
Mixed Homophily	M-rbmforAttribute_Exec		Increased probability of a friendship tie reciprocated with an esteem tie, and vice versa, where both actors are in the executive committee/where both actors are not in the executive committee
Heterophily	rbDiffAofContinuous Attribute_Age rbDiffAofContinuous Attribute_Income		The greater the difference in the age of both actors, the greater the probability of a friendship tie The greater the difference in the income of both actors, the greater the probability of a friendship tie

[*] This parameter was not included in the model because graph density as fixed.
Notes: 1. A solid arrow represents an affect/disaffect tie while a dotted arrow represents an esteem/disdain tie. 2. Two strokes on a tie represents the absence of that tie. 3. For a complete list of parameters and more detailed explanations on each parameter refer to the "PNet User Manual" available here: http://sna.unimelb.edu.au/__data/assets/pdf_file/0006/662865/PNetManual.pdf (Wang et al., 2006a,b).

and we want to be friends with those we admire. Similarly, we tend to disdain those we dislike, and dislike those we disdain. In Models 3 and 4, the model takes into account the interdependence of positive and negative ties. This again makes intuitive sense, as those we like tend to influence who we dislike, and vice versa.

Our XPNet models were estimated on a dataset that combined both the 3rd and 4th year networks. Since actors were restricted to nominating only those in their cohort, we imposed a structural zero matrix to replicate that effect in the models. In essence we forced XPNet to only form ties within each cohort.

The parameters in our models were selected through an iterative process, starting with the lowest order (simplest) parameters such as reciprocity, keeping parameters that are statistically significant, and adding progressively higher-order parameters until the goodness of fit analysis shows that the model is a good fit of the data. We also fixed graph density to facilitate model fit. Hence there are no Arc A and Arc B parameters in the models.

3.3. *Further analysis*

We are interested in not just individual parameters, but also identifying trends in the larger scale mechanisms which are driving positive and negative ties. To facilitate this analysis we created Table 2 which defines a classification system for various type of parameters, based on common underlying mechanisms widely recognised in past research (Robins et al., 2009; Robins and Lusher, 2013). We categorise parameters into six mechanisms of tie formation: (1) reciprocity; (2) entrainment; (3) activity; (4) popularity; (5) closure (triadic and 4-cycle); and (6) homophily.

4. Results

The results comprise of five sections: (1) descriptive statistics, with a comparison of the observed networks to a simple random graph model; (2) ERG model parameter estimates; (3) ERG model goodness of fit (GOF) statistics; (4) a test for dominant mechanisms driving ties in each network; and (5) an explanation of the dominant mechanisms.

In this paper, sub-sections 4.1, 4.2, and 4.3 pertain only to Models 1 and 2, as the same information for Models 3 and 4 have already been reported in a previous paper (Yap and Harrigan, 2015).

4.1. *Descriptive statistics*

Table 3 shows the descriptive statistics of our dataset. There were 282 participants in our study, from a total potential pool of 298. Participants sent 987 affect ties, 540 esteem ties, 499 disaffect ties, and 394 disesteem ties. The sample included 181 females, and 101 males. People of Chinese ethnicity comprised the majority (225) with small percentages of Indians, Malays, and other races. 18 respondents were former members of the executive committee of the Social Science Society (abbreviated as 'exec' in models), which represents the student body and has social and welfare responsibilities.

Before analysing our networks, it is important to establish that the affect and esteem networks are in fact distinct from one another. One criticism that could be levelled at our data is that the affect and esteem networks are largely synonymous. To test this we examined the entrainment of ties (Table 4).

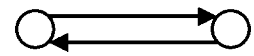
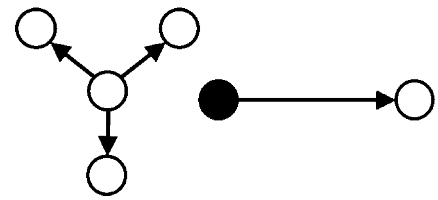
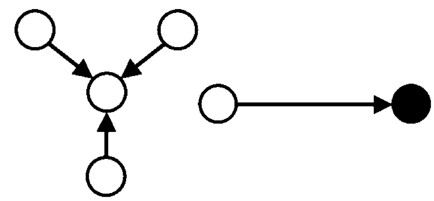
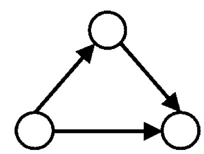
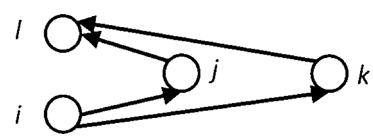
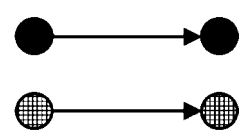
Table 4 shows the number of entrained ties for each pair of networks, the Pearson's/Cramer's correlation, and Tetrachoric coefficient between each pair of networks. We note that in Table 4, nearly 30% of positive and negative esteem ties are entrained with positive and negative affect ties respectively.

There are two main conclusions that can be drawn from Table 4. First, the networks which are most similar to each other are networks of the same sign (i.e. positive networks are correlated with positive networks, and negative networks are correlated with negative networks). Second, this correlation between the two positive networks, and the two negative networks, suggests that while the networks are interdependent, they also measure different types of relationships.

Tables 5 and 6 show a comparison of the observed networks with a sample of 1000 random graphs of the same density. Where the observed count is higher than the sample mean, there is a tendency towards forming this subgraph. Where the observed count is lower than the sample mean, there is a tendency against forming this subgraph. In these models, A ties are affect (friendship) ties (like/dislike), and B ties are esteem (status) ties (esteem/disesteem).

When reading Tables 5 and 6 significant differences between the observed count and the sample mean is indicated by an absolute t-statistic larger than 2. Since we cannot necessarily assume that

Table 2
Definitions of mechanisms.

Mechanisms	Definition	Sample subgraph
Control	Parameters included in the model to control for the effects of the survey design, including the skew of outdegree distribution.	NA
Reciprocity	Parameters where a tie with a second party predicts the return of a complementary tie.	
Entrainment	Parameters where a tie in one network predicts the formation of the same tie in another network.	
Activity	Parameters where either an outgoing tie or an attribute predicts the formation of outgoing ties.	
Popularity	Parameters where either an incoming tie or an attribute predicts the formation of incoming ties.	
Closure (triadic)	Parameters where ties with a common third party is associated with the formation of a tie.	
Closure (4-cycles)	Parameters where opposite sides of a 4-cycle are dependent on each other when the other two sides of the 4-cycle are present (Koskinen and Daraganova, 2013).	
Homophily	Parameters where network ties tend to occur between individuals with similar actor attributes (Robins and Daraganova, 2013).	

the underlying distribution of graphs is normally distributed, we use the *t*-statistic of 2 as a rule of thumb for assessing statistical significance.

A brief review of the positive ties model reveals that approximately 30% of parameters have a *t*-statistic of 2 or less; approximately another 30% have t-statistics between 2 and 12, and the remaining 40% have *t*-statistics over 12. A similar review of the negative ties model reveals that approximately 40% of parameters have a *t*-statistic of 2 or less; approximately another 40% have a *t*-statistic between 2 and 12, and the remaining 20% have a *t*-statistic over 12. These high *t*-statistics are to be expected in a comparison of an observed network and a sample of pure random graphs, because in real networks many network effects are likely to be mutually reinforcing.

4.2. *ERG model parameter estimates*

Tables 7 and 8 show the converged and fitted ERG models for positive and negative ties. The parameters and standard error can be read as per a standard logistic regression. The star in the last column of our table indicates that the *t*-statistic (parameter value divided by standard error) is greater than 2.

Both models are fully converged. The convergence statistic in ERGMs is used to test whether the model is a good fit for the observed dataset. 2000 sample graphs were generated using the estimated parameters, and the mean graph statistics of these sample graphs were compared to the observed network. The convergence statistic was calculated by dividing the difference between the observed and mean simulated graph statistics by the standard deviation of the mean of the simulated graph statistics. This convergence statistic is very similar to the *t*-statistic in a baseline random graph model. For parameters in the model, this convergence statistic should ideally be below 0.1, and definitely below 0.2 (by convention). The convergence statistics for all parameters in both our models are below 0.1.

Comparing Tables 7 and 8, it is clear that the positive network has considerably more significant parameters (as indicated by the *) than the negative network. This points to the generally increased complexity of, and number of different mechanisms driving, positive tie networks.

4.3. *Goodness of fit (GOF) statistics*

We test the adequacy of our ERG models by conducting a goodness of fit test. This test involves simulating the network using the

Table 3
Descriptive statistics for the observed networks.

	Year 3	Year 4	Total
No. of students	139	159	298
No. of participants	132	150	282
Positive affect network			
Ties	486	501	987
Average degree	3.7	3.3	3.5
Density	0.028	0.022	0.025
Negative affect network			
Ties	237	262	499
Average degree	1.8	1.7	1.8
Density	0.014	0.012	0.013
Positive esteem network			
Ties	270	270	540
Average degree	2.0	1.8	1.9
Density	0.016	0.012	0.014
Negative esteem network			
Ties	184	210	394
Average degree	1.4	1.4	1.4
Density	0.011	0.009	0.010
Female	71	110	181
Males	61	40	101
Chinese	99	126	225
Indian	14	11	25
Malay	8	5	13
Eurasian	1	3	4
Others	10	5	15
Held positions in Student Welfare Exco Committee	10	8	18

Table 4
(i) Number of entrained ties, (ii) Pearson's/Cramer's Correlation, and (iii) Tetrachoric Correlation of ties in positive and negative affect and esteem networks.

	Total number of ties	Number of entrained ties			
		Positive affect	Negative affect	Positive esteem	Negative esteem
Positive affect	987	–	–	–	–
Negative affect	499	0 -0.017^{***} -1.000^{***}	–	–	–
Positive esteem	540	159 0.203^{***} 0.594^{***}	7 0.001 0.016	–	–
Negative esteem	394	18 0.014^{**} 0.113^{*}	114 0.264^{***} 0.702^{***}	0 -0.012^{*} -1.000^{*}	–

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

estimated parameters, and then comparing the fit of the simulated graphs with the observed graph, for parameters in the model and parameters not in the model.

The rule of thumb used for GOF tests is: for parameters in the model, the convergence statistic should ideally be below 0.1, and definitely below 0.2; and for parameters not in the model, the convergence statistic should ideally be below 2.

The GOF tables are provided for readers here: [http://tinyurl.com/HY2016GOF].

In the positive tie network, all parameters in the model are fitted, and 9 of the parameters not in the model are not fitted. 1 of the parameters (T1AU12A) not in the model has a convergence statistic above three. Given the large number of parameters both in the model (34) and not in the model (146) – a total of 180 – having 9 parameters which do not fit is acceptable.

In the negative tie network, all parameters in the model are fitted, and 9 of the parameters not in the model are not fitted. None of the parameters not in the model have convergence statistics above three. As before, since there are a total of 180 parameters either in the model or not in the model, having 9 parameters which do not fit is acceptable. Note that there is no overlap in the 9 parameters which are not converged in each model.

Table 5
Comparison of key parameters in the positive network to a baseline random graph model.

Parameters	Observation	Sample mean	Std dev.	t-Statistic[a]
ArcA	987	987.0	0.000	–
ReciprocityA	232	12.4	3.462	63.444
030TA	743	85.5	9.518	69.079
030CA	173	28.5	5.220	27.675
AKT-TA(2.00)	601	83.7	9.157	56.506
AKT-CA(2.00)	424	83.8	15.043	22.626
AKT-DA(2.00)	556	83.7	9.166	51.531
AKT-UA(2.00)	610	83.7	9.128	57.658
SameCategoryAReciprocity_Race	134	7.1	2.600	48.804
SameCategoryAReciprocity_First_SOSS_Major	94	4.4	2.020	44.353
DifferentCategoryAReciprocity_Race	98	5.2	2.341	39.624
DifferentCategoryAReciprocity_First_SOSS_Major	138	8.0	2.807	46.331
ArcB	540	540.0	0.000	–
2-In-StarB	1559	514.1	22.718	45.992
3-In-StarB	4665	324.9	47.129	92.089
K-In-StarB(2.00)	604	383.8	9.606	22.946
A2P-UB(2.00)	1525	510.8	22.460	45.164
ArcAB	159	13.6	3.550	40.955
ReciprocityAB	119	13.4	3.581	29.501
ReciprocityAAB	83	0.3	0.570	145.095
ReciprocityABB	19	0.2	0.423	44.481
ReciprocityAABB	8	0.0	0.050	160.110
In2StarAB	2822	1883.4	43.660	21.499
TABA	213	47.1	7.066	23.472
TABB	184	25.6	5.150	30.751
TAAB	199	47.2	6.918	21.942
TBAA	215	46.9	6.908	24.340
TKT-ABA(2.00)	186	46.1	6.817	20.521
UKT-ABA(2.00)	185	45.9	6.646	20.861
mrs_Gender	87	8.8	2.888	27.081
mrr_Gender	90	8.9	2.914	27.828
mrr_Exec	28	0.8	0.928	29.283
exab_Gender	73	8.7	2.926	21.964
exab_Exec	29	0.8	0.901	31.303
mrb_Gender	58	5.9	2.368	22.008
mrb_Exec	9	0.1	0.230	38.916
mrbm_Exec	7	0.1	0.222	31.258
msum_Age	11,860	5193.5	161.558	41.263
msum_Income	1339	581.5	19.813	38.229
mdiff_Age	364	170.4	6.590	29.382
mdiff_Income	311	139.7	6.899	24.835
SameCategoryArcAB_Race	91	7.8	2.745	30.296
SameCategoryArcAB_First_SOSS_Major	71	4.8	2.171	30.481
DifferentCategoryArcAB_Race	68	5.8	2.367	26.298
DifferentCategoryArcAB_First_SOSS_Major	88	8.8	2.911	27.213
SameCategoryReciprocityAB_Race	64	7.7	2.696	20.896
SameCategoryReciprocityAB_First_SOSS_Major	51	4.8	2.167	21.316
DifferentCategoryReciprocityAB_Race	55	5.7	2.344	21.027
DifferentCategoryReciprocityAB_First_SOSS_Major	68	8.6	2.897	20.511

Note: This table only shows the key parameters with a high t-statistic. For a full comparison, please contact the authors of this paper.
[a] $t-Statistic = \frac{observation-sample\ mean}{standard\ deviation}$.

4.4. *Testing for dominant mechanisms*

Table 9 categorises each of the significant parameters in our four models according to the mechanisms in Table 2.

Table 10 summarises the findings of Table 9. Table 10 shows the count of significant positive, negative, and mixed-sign parameters in each of the four models, with parameters classified under each mechanism. This count gives a sense of which mechanisms are likely to be driving tie formation in each network.

What is readily apparent in Table 10 is the almost complete absence of negative tie parameters measuring reciprocity, closure and homophily, especially as compared to the positive tie parameters.

4.5. *Explaining the dominant mechanisms*

While entrainment, activity, and popularity are prevalent in both the positive tie and negative tie network parameters; closure, reciprocity, and homophily are present in the positive tie network parameters, but almost entirely absent in the negative tie network parameters. We compare positive tie and negative tie parameters more closely for each of these three mechanisms.

4.5.1. *Closure*

Closure in our models is measured using the alternating-k parameters for triads and paths. As a result, our triadic parameters also measure four-cycle effects: the sides of an alternating-k triangle are composed of multiple four-cycles.

We find that triadic and four-cycle closure effects are strong and important within the positive tie network parameters, but are almost completely absent in the negative tie networks. The 13 significant positive network parameters that measure closure/anti-closure can be generally categorised into: transitive triadic closure (e.g. AKT-TA), cyclical triadic anti-closure (e.g. AKT-CA), and transitive four-cycle anti-closure (e.g. A2P-TA). In contrast, the only significant negative network parameter measuring closure/anti-closure is a triadic anti-closure mechanism (AKT-DB in Model 3).

Table 6
Comparison of key parameters in the negative network to a baseline random graph model.

Parameters	Observation	Sample mean	Std dev.	*t*-Statistic[a]
ArcA	465	465.0	0.000	–
2-In-StarA	1208	381.1	19.770	41.825
3-In-StarA	3574	207.7	35.592	94.581
K-In-StarA(2.00)	486	295.5	9.269	20.532
A2P-UA(2.00)	1181	379.3	19.592	40.932
ArcB	380	380.0	0.000	–
2-In-StarB	776	254.1	15.955	32.709
3-In-StarB	1880	112.4	23.577	74.969
A2P-UB(2.00)	768	253.3	15.878	32.416
ArcAB	114	4.4	2.088	52.488
ReciprocityAAB	8	0.1	0.256	31.040
ReciprocityABB	9	0.0	0.205	43.707
ReciprocityAABB	3	0.0	0.032	94.860
In2StarAB	1718	624.3	25.252	43.309
mrs_Gender	77	2.8	1.695	43.763
mrr_Gender	62	2.9	1.709	34.610
mrr_Exec	20	0.3	0.518	38.092
mrb_Gender	48	1.9	1.396	33.048
msum_Age	5661	650.2	94.906	52.798
msum_Income	650	70.4	12.054	48.079
mdiff_Age	147	13.0	3.764	35.600
mdiff_Income	176	19.7	4.083	38.293
SameCategoryArcAB_Race	67	2.5	1.571	41.071
SameCategoryArcAB_First_SOSS_Major	40	1.6	1.215	31.636
DifferentCategoryArcAB_Race	47	1.9	1.370	32.920
DifferentCategoryArcAB_First_SOSS_Major	74	2.8	1.690	42.117

Note: This table only shows the key parameters with a high *t*-statistic. For a full comparison, please contact the authors of this paper.
[a] $t - Statistic = \frac{observation - sample\ mean}{standard\ deviation}$.

Table 7
ERG model of positive network.

	Parameter	Std err.
ReciprocityA	3.434	0.160*
SinkA	−1.381	1.093
SourceA	−0.637	0.447
IsolatesA	−0.494	1.155
In-K-StarA(2.00)	0.387	0.172*
Out-K-StarA(2.50)	−0.537	0.137*
AKT-TA(2.00)	1.252	0.069*
AKT-CA(2.00)	−0.331	0.071*
A2P-TA(2.00)	−0.152	0.019*
rbAforAttribute_Gender	0.141	0.063*
rbAforAttribute_Exec	0.651	0.170*
rrAforAttribute_Exec	0.200	0.112
rbDiffAofContinuousAttribute_Age	−0.050	0.025*
rbDiffAofContinuousAttribute_Income	−0.092	0.022*
SameCategoryArcAforAttribute_First_SOSS_Major	0.175	0.050*
ReciprocityB	0.021	0.352
SinkB	−3.963	0.588*
SourceB	−1.756	0.413*
IsolatesB	−5.622	0.755*
In-K-StarB(2.00)	1.971	0.193*
Out-K-StarB(2.50)	0.765	0.145*
AKT-TB(2.00)	0.522	0.119*
AKT-CB(2.00)	−0.253	0.169
A2P-TB(2.00)	−0.065	0.022*
rbBforAttribute_Gender	−0.214	0.075*
rbBforAttribute_Exec	1.156	0.268*
rrBforAttribute_Exec	0.473	0.094*
ArcAB	2.208	0.159*
ReciprocityAB	1.337	0.182*
Mixed2StarBA	−0.004	0.015
TKT-ABA(2.00)	0.386	0.108*
CKT-ABA(2.00)	−0.464	0.133*
M-rrforAttribute_Exec	−0.934	0.276*
M-rbmforAttribute_Exec	−1.444	0.513*

* $t - Statistic = \frac{Parameter}{standard\ error} \geq 2$.

Table 8
ERG model of negative network.

	Parameter	Std err.
ReciprocityA	−0.074	0.503
SinkA	−4.399	0.459*
SourceA	−1.035	0.366*
IsolatesA	−5.353	0.584*
In-K-StarA(2.30)	1.381	0.149*
Out-K-StarA(2.00)	1.876	0.199*
AKT-TA(2.00)	0.333	0.170
AKT-CA(2.00)	−0.127	0.234
A2P-TA(2.00)	0.007	0.024
rrAforAttribute_Exec	0.408	0.107*
ReciprocityB	0.382	0.522
SinkB	−4.604	0.474*
SourceB	−1.281	0.383*
IsolatesB	−5.862	0.606*
In-K-StarB(2.30)	1.403	0.164*
Out-K-StarB(2.00)	2.014	0.250*
AKT-TB(2.00)	0.040	0.242
AKT-CB(2.00)	−0.236	0.348
A2P-TB(2.00)	0.025	0.035
rbBforAttribute_Exec	0.249	0.558
rrBforAttribute_Gender	−0.107	0.081
rrBforAttribute_Exec	0.373	0.137*
rbSumBofContinuousAttribute_Age	0.019	0.026
ArcAB	3.483	0.138*
ReciprocityAB	1.352	0.341*
Mixed2StarAB	−0.034	0.029
Mixed2StarBA	−0.044	0.027
TKT-ABA(2.00)	0.204	0.210
CKT-ABA(2.00)	−0.134	0.408
M-rrforAttribute_Exec	−0.934	0.312*
M-rbmforAttribute_Exec	0.359	1.104

* $t - Statistic = \frac{Parameter}{standard\ error} \geq 2$

4.5.2. *Reciprocity*

Reciprocity in our models measures simplex reciprocity (i.e. a tie is reciprocated by a tie in the same network, e.g. affect with affect) and multiplex reciprocity (i.e. a tie is reciprocated by a tie in another network, e.g. affect with esteem, or affect with disaffect).

There are five significant positive tie reciprocity parameters, and two significant negative tie reciprocity parameters. We find both simplex reciprocity (e.g. Reciprocity A) and multiplex reciprocity

Table 9
Classification of significant parameters.

	Model 1 (Positive Network) A: Affect B: Esteem	Model 2 (Negative Network) A: Disaffect B: Disesteem	Model 3 (Affect Network) A: Affect B: Disaffect	Model 4 (Esteem Network) A: Esteem B: Disesteem	Control	Reciprocity	Entrainment	Activity	Popularity	Closure	Homophily
ReciprocityA	3.43	–	3.67	1.38		√					
SinkA	–	−4.40	–	−4.17	√			√	√		
SourceA	–	−1.04	–	−1.62				√	√		
IsolatesA	–	−5.35	–	−5.73	√			√	√		
In-K-StarA	0.39	1.38	0.47	1.88					√		
Out-K-StarA	−0.54	1.88	−0.80	0.95	√			√			
AKT-TA(2.00)	1.25	–	0.59	–				√	√	√	
AKT-CA(2.00)	−0.33	–	−0.42	–						√	
AKT-UA(2.00)	–	–	0.69	–				√		√	
AKT-DA(2.00)	–	–	–	0.85					√	√	
A2P-TA(2.00)	−0.15	–	−0.15	−0.08				√	√	√	
rrAforAttribute_Exec	–	0.41	–	0.31					√		
rbAforAttribute_Gender	0.14	–	0.59	–							√
rbAforAttribute_Exec	0.65	–	0.74	1.00							√
rbDiffAofContinuousAttribute_Age	−0.05	–	–	–							√
rbDiffAofContinuousAttribute_Income	−0.09	–	−0.09	−0.09							√
Same Category ArcA for Attribute_Race	–	–	–	−0.21							√
SameCategoryArcAforAttribute_First_SOSS_Major	0.17	–	0.17	0.20							√
ReciprocityB	–	–	–	1.38		√					
SinkB	−3.96	−4.60	−4.62	−4.79	√			√	√		
SourceB	−1.76	−1.28	−1.82	−2.24				√	√		
IsolatesB	−5.62	−5.86	−6.31	−6.96	√			√	√		
In-K-StarB	1.97	1.40	2.02	2.21					√		
Out-K-StarB	0.77	2.01	2.04	2.14	√			√			
AKT-TB(2.00)	0.52	–	–	–				√	√	√	
AKT-DB(2.00)	–	–	−0.63	–					√	√	
A2P-TB(2.00)	−0.06	–	–	–				√	√	√	
rbBforAttribute_Gender	−0.21	–	0.65	–							√
rsB for Attribute_Gender	–	–	−0.41	–				√			
rrB for Attribute_Gender	–	–	−0.46	−0.31					√		
rbBforAttribute_Exec	1.16	0.37	–	–							√
rrBforAttribute_Exec	0.47	–	0.33	0.29					√		
rbDiffB of Continuous Attribute_Age	–	–	0.06	–							√
ArcAB	2.21	3.48	–	–			√	√	√		
ReciprocityAB	1.34	1.35	–	0.88		√					
TKT-ABA(2.00)	0.39	–	–	0.47				√	√	√	
CKT-ABA(2.00)	−0.46	–	–	–						√	
UKT-ABA(2.00)	–	–	–	0.31				√		√	
DKT-BAB(2.00)	–	–	–	0.50					√	√	
M-diffm for Attribute_Age	–	–	0.40	–		√					√
M-rrforAttribute_Exec	−0.93	−0.93	–	–				√	√		
M-rbmforAttribute_Exec	−1.44	–	–	–		√					√

Table 10
Count of significant parameters for each mechanism.

	Model 1	Model 2	Models 3 and 4		
	Positive-tie parameters	Negative-tie parameters	Positive-tie parameters	Negative-tie parameters	Mixed-sign parameters
Popularity	11	7	8	9	2
Activity	8	4	5	3	2
Entrainment	2	2	–	–	–
Reciprocity	3	1	2	1	2
Closure	7	0	6	1	3
Homophily	8	1	8	2	1
Total (excluding controls)	23	9	20	13	5

(e.g. Reciprocity AB) in both positive and negative tie network parameters.

4.5.3. Homophily

Homophily in our models is mainly measured using demographic attributes. The limitation of this is that there could be homophily effects on other dimensions (such as psychological, behavioural, institutional, etc.) that are not captured.

There are 16 significant positive tie homophily parameters (e.g. homophily on affect for exec – membership of executive committee of student society), and only three significant negative tie homophily parameters (e.g. homophily on disaffect for gender).

5. Discussion

Theorising of negative ties has tended to focus on either the internal dynamics of simplex negative tie networks, or on the interactive effects in multiplex signed tie (positive and negative) networks. We propose that there is merit in looking at how positive and negative ties – particularly those which are found on the same set of actors – have very different fundamental dynamics.

While our study does find interdependence between positive and negative networks (one mixed-sign parameter is significant in Model 3, and four in Model 4), the internal dynamics of the positive and negative networks dominate the tie formation/dissolution dynamics (for example, 18 single-sign, non-control parameters are significant in Model 3, and 15 single-sign, non-control parameters are significant in Model 4). We also note that the addition of mixed-sign parameters to the models (in Models 3 and 4, as against Models 1 and 2) has only marginal impacts on the magnitude and significance of the single-sign parameters (see Table 9).

Our study finds that while positive tie formation is driven by a range of at least six mechanisms, negative tie formation is driven by only a subset of those mechanisms. We find that popularity, activity, and entrainment are significantly present in both the positive and negative network parameters. In contrast, reciprocity, closure, and homophily are largely absent in the negative tie network parameters.

We argue that the overriding reason that closure, reciprocity, and homophily do not drive negative tie formation is because an important element of negative sentiment is avoidance. In our networks, this seems to play out in two ways. For closure and reciprocity, avoidance leads to low information transfer through negative ties, and thus, lack of dyadic or triadic dependency between negative ties. For example, if I dislike someone, and therefore avoid them, the dislike is less likely to be reciprocated because my avoidance means less opportunities to interact. For homophily, avoidance creates something of a natural short circuit on any attributes with low salience negative sentiment in a network. For example, while a small positive sentiment between people of the same gender may over time lead to the creation of close friendships, a small negative sentiment may lead to low level avoidance, distance, and null ties. Thus, where attributes generate small negative homophilous/heterophilous sentiments, avoidance tends to result in absent ties rather than negative ties. Negative tie heterophily is, thus, expected to be only found on highly conflictual attributes, such as race in a racially polarised society.

5.1. Comparing our findings to the literature

For closure, our findings are in line with the existing literature (although it should be noted that this was not the focus of the other studies cited): Ellwardt et al. (2012), Huitsing et al. (2012), and Boda and Néray (2015) find weak or no triadic closure in negative tie networks. Ellwardt et al. (2012), and Boda and Néray (2015) also find weak or no negative tie four-cycle anti-closure in line with our findings. Papachristos et al. (2013) had mixed findings with one dataset agreeing with our findings (and finds no closure) while the other contradicts our findings (and finds triadic anti-closure, which suggests balance theory is in operation).

For reciprocity, our findings seem to differ from the existing literature in that while we do not find substantial reciprocity in the negative tie networks, most other literature does (Ellwardt et al., 2012; Huitsing et al., 2012; Boda and Néray, 2015; Papachristos et al., 2013). There are two things to note. First, our data does find some reciprocity within the negative tie networks, just less than in the positive tie networks. Second, some literature has found that reciprocity, while present in the negative tie network, is weaker than in the positive tie network (Huitsing et al., 2012; Boda and Néray, 2015).

For homophily, our findings indicate the complete absence of negative tie heterophily (out-group dislike). This differs from the existing literature where negative tie heterophily is prevalent. We attribute this to the fact that most studies on negative tie homophily focus on conflictual attributes: race (Lusher et al., 2013), religious diversity (Nieuwenhuis et al., 2013), ethnicity (Boda and Néray, 2015), and ethnicity and immigrant origins (Jaspers et al., 2013). We argue the lack of negative tie heterophily in our data occurs because none of the attributes which we collected are 'conflictual' or 'polarizing' attributes. Instead, these attributes created at most a low level of negative sentiment, which would lead to avoidance rather than active negative ties.

Note we do not make a claim that in other social contexts these same attributes would remain non-conflictual. Of course, these attributes may be conflictual in other social contexts. For instance, attributes like race and gender, in particular, can be very conflictual in certain social contexts. In these contexts, one would expect to find negative network heterophily driven by out-group dislike.

Our data also shows some negative tie homophily (in-group dislike): on gender, membership in student council executive, and age. While the literature has found this, it is mainly found on geographical propinquity: gangs sharing turf boundaries tend to shoot each other (Papachristos et al., 2013), while colleagues in the same work group tend to gossip negatively about each other (Ellwardt et al., 2012). In this case, avoidance is not possible due to close propinquity and the consequent competition for scarce resources (e.g. territory for gangs).

5.2. Theoretical explanations of the differences between positive and negative tie networks

It remains to explain why these differences between positive and negative networks occur. Before we provide what we think is the most plausible explanation, we want to address several competing explanations: (1) the sparseness of negative ties; (2) the randomness of negative ties; and (3) positive–negative asymmetry.

First, the sparseness of negative ties may explain the lack of closure, reciprocity, and homophily in negative ties. In most studies negative ties are considerably less prevalent than positive ties. Such sparseness, theoretically, is likely to lead to less scope for tie interdependence, and therefore complex mechanisms like closure, reciprocity, and homophily. In our case, we don't believe this is likely as our negative tie networks have a total of 893 ties and about half the density of our positive tie network. This should be more than adequate for complex mechanisms to emerge.

Second, the randomness of negative ties poses an alternative explanation. Participants may have nominated their negative ties at random. However, if this were true, we should have found other mechanisms to be absent as well. Instead, we found strong effects of popularity, activity, and entrainment.

Third, positive-negative asymmetry, as described in the social psychology literature on intergroup conflict, may explain the differences between the mechanisms driving positive tie and negative tie networks. Positive-negative asymmetry research shows that humans tend to show most intergroup bias as ingroup preference rather than as outgroup hostility (Hewstone et al., 2002). Normative constraints make it difficult to justify harm (in our case negative ties) towards others solely on the basis of out-group membership. While this might explain some of the lack of negative tie heterophily (outgroup bias), it does not explain the lack of closure, reciprocity, and negative tie homophily (ingroup dislike).

Our preferred theoretical explanation incorporates the insights of positive-negative asymmetry research, but extends it. We argue that the lack of closure, reciprocity and homophily is largely a product of humans' tendency to try to avoid those with whom they feel negative sentiments. Dislike and disesteem generally invokes a desire to create distance and an avoidance of one's tie partners (Jehn, 1995; Thibaut and Kelley, 1978; Labianca and Brass, 2006). This tendency to avoid has two main effects: (1) it lowers information transfer along negative ties; and (2) is a natural short-circuiting of cumulative causation in situations of negative sentiment.

5.2.1.1. Avoidance and low information transfer

We argue that the lack of closure and reciprocity in the negative tie network is largely because humans' tendency to avoid the recipients of their negative ties leads to low information transfer through those negative ties. In the case of closure, it is unlikely that information will transfer through two or more adjacent negative ties where tie partners are actively avoiding each other. While we may tell our friends about the people we dislike, we do not pass that information onto our enemies (McAndrew et al., 2007). In fact, Grosser et al. (2010) found that affective trust, not just friendship, is required for the transmission of negative gossip. In the case of reciprocity, as one avoids the recipient of their negative tie, it is quite possible (and it seems quite common) that the recipient of that tie remains unaware of dislike being directed towards them. One is unlikely to reciprocate a negative tie that one is unaware of.

5.2.1.2. Avoidance as a natural short circuit

We argue that the lack of homophily in the negative tie network arises because the tendency towards avoidance short-circuits the formation of intense negative ties on low salience attributes. In fact, Paladino and Castelli (2008) found that mere classification based on trivial differences was sufficient to trigger immediate and spontaneous avoidance of the outgroup. We argue that low salience attributes which display negative sentiment rarely get the chance to snowball into a fully-fledged negative tie. This is because the initial small negative sentiment encourages avoidance, which allows the negativity to peter out. In contrast, low salience attributes that display positive sentiment can create 'virtuous cycles', with small positive sentiments leading to the formation of substantial positive ties via cumulative causation (Clark and Drewry, 1985; McPherson et al., 2001; Reagans, 2011; Amichai-Hamburger et al., 2013). Similar 'vicious cycles' are not expected to exist in negative tie networks unless the attributes are highly salient. We call such highly salient attributes 'conflictual' or 'polarizing' attributes, because the strong negative sentiment that they create overcomes the tendency towards avoidance and generates active hostility.

5.3. Limitations

The findings of this study need to be qualified in a number of ways. Firstly, signed social network ties cover an incredibly diverse range of human interactions, from avoidance and gossip to homicide and war. In the particular case of this study our dataset is one that is made of university students, in an Asian context, and the underlying social dynamics of our population are potentially very different to those in the other studies cited. Studies we draw comparisons to vary in the nature of the ties measured (e.g. avoidance, gossip, bullying, murder), the demographic characteristics of respondent's (children, adolescents, undergraduates, working adults) and the settings (schools, universities, neighbourhoods, workplaces). Any attempt to generalise across such a range should take into consideration the vast differences in the nature of these ties, populations, and settings. Nonetheless, we believe the goal of generalisable knowledge necessitates attempting to find patterns across diverse but related phenomena.

In addition, this study is cross-sectional (single time point), and because of this inference is limited to correlations, without the time order and greater causal inference that longitudinal data would provide.

6. Conclusion

The challenge we set at the beginning of this paper was to characterise and explain the fundamental difference between positive and negative tie networks, particularly those found on the same set of actors.

We found that closure, reciprocity, and homophily were considerably weaker and sometimes absent from negative tie networks. We argue that the key explanation for this lies in the importance of avoidance inherent in the nature of negative ties. This avoidance leads to two main effects: low information transfer resulting in the absence of closure and reciprocity mechanisms, and a short-circuiting of cumulative causation on low salience attributes leading to an absence of homophily mechanisms in negative ties. We recognise that the existing literature does find evidence of both homophily and heterophily in negative tie networks; however, we argue that these studies tend only to be found under two main conditions: propinquity (for homophily) and conflictual attributes (for heterophily).

How are these findings likely to play out in everyday life? Unless negative ties are highly conflictual – like overt racism, inter-gang homicide, or perhaps public bullying – or they are the result of serious competition and propinquity – such as individuals in the hothouse of a reality TV game – there is likely to be very little community formation that is itself the product of negative ties. Negative ties are unlikely to be directed towards people holding different traits/attributes (homophily), or even to those who are directing negative ties at oneself (reciprocity), and negative ties are unlikely to form 'circular firing squads' (closure). Instead, negative ties are likely to be concentrated on a relatively small number of dispersed individuals who are the recipients of many negative ties. They are likely to be disliked by a diverse range of people who are more or less unrelated.

In this type of situation, what is interesting is not just what is observed, but also what is not observed. In offices, schools, religious organisations we will observe considerable group formation on a variety of traits like gender, race, and role. But if these traits are not conflictual, then there is unlikely to be animosity between members of these groups. We will observe negative sentiments and dislike, but these will be largely directed to a small number of unpopular individuals, who themselves are largely disconnected, and these individuals are unlikely to reciprocate the negative sentiments felt towards them. More generally, interpersonal mutual dislike – which we associate with feuds between individuals or nations - should be rare.

It must be noted that this dynamic is probably constrained to a particular class of negative tie networks: ones where ties do not represent highly overt aggression. Instead these dynamics are much more the dynamics of negative ties in a more-or-less harmonious environment. In such an environment, negative ties tend not to polarise, or factionalize, or lead to interpersonal feuds, but rather negative ties accumulate to a small but diffused set of persons at the bottom of the social heap.

Future research is likely to benefit by moving in a number of different directions. First, the exploration of other 'flavours' of positive and negative ties seems important. This study has focused on only affect and status, but there are many others. Second, it seems vital to explore homophily on negative ties in greater depth. This study found virtually no homophily on negative ties, and future research should aim to find out whether this is a larger trend, or just a function of the attributes we measured. Such research could test the theory of negative tie heterophily on conflictual or polarising attributes. Finally, it seems important to explore the dynamics of negative ties under different conditions, particularly comparing conditions of relatively harmony and overt competition, and comparing ties such as private judgments and hostile public acts.

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